UNEMPLOYMENT, PARTICIPATION AND WORKER FLOWS OVER THE LIFE-CYCLE*

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We estimate life-cycle transition probabilities among employment, unemployment and inactivity for US workers. We assess the importance of each worker flow to account for participation and unemployment rates over the life cycle. We find that inactivity exit and entry matter but the empirically relevant margins defy conventional wisdom: high youth unemployment is due to high employment exit probabilities, while low labour force entry probabilities substantially account for low participation and unemployment among older workers. Our results remain intact under several forms of heterogeneity, time-aggregation bias and misclassification errors.

Labour market experiences vary significantly over the life cycle: unemployment rates are higher for younger individuals while participation rates fall dramatically for workers after a certain age. In this article, we identify the worker flows that generate these differences in unemployment and participation between age groups. In doing so, we are able to answer the following types of questions: is high unemployment among the young a result of high job separation or low job finding probabilities? Are transitions in and out of the labour force important in shaping life-cycle work patterns?

We estimate transition probabilities between employment (E), unemployment (U) and inactivity/out of the labour force (O) over the life cycle, using Current Population Survey (CPS) monthly data for male and female workers.[1] We then propose a methodology based on Markov chains of order one to account for the relative importance of each of these transition probabilities in shaping the life-cycle profiles of unemployment and participation rates. Our main findings are that the participation margin, i.e. movements in and out of the inactivity state, is key to explain high unemployment and low participation of the young population and low participation and unemployment among the population older than 50. We find a negligible role for

[1] In terms of methodology, we follow a rich literature examining the cyclical behaviour of worker flows. See for example Abowd and Zellner (1985), Darby *et al.* (1986), Davis (1987), Blanchard and Diamond (1990), Hall (2006), Shimer (2012), Fujita and Ramey (2009) and Elsby *et al.* (2009).

the job finding rate, which is surprising, given its importance in the business cycle literature (Shimer, 2012).

The fact that transitions to and from inactivity matter for the evolution of unemployment and participation is natural in a life-cycle context[2], because workers start and finish their lives as inactive: they transit from inactivity into the labour force at the beginning of the life cycle and re-enter to inactivity at the end. Thus, changes in the labour force entry margin should explain participation and unemployment of the young, while changes in the exit margin should generate lower participation (and unemployment) among the older population. However, our results show that the relevant margins actually operate in the opposite direction: the exit margin matters most for the young, while the entry margin affects older workers.

Our results should inform current life-cycle search models, since the facts we present are useful to discipline and tease out different theories from the data.[3] Given our results regarding young workers, search theories need to explain why labour force exit rates are high for this group of the population. For example, both Esteban-Pretel and Fujimoto (2011) and Menzio et al. (2012) present quantitative models that fit the facts with respect to high youth unemployment. Although their methodologies differ,[4] both papers rely only on age differences in employment-to-unemployment (EU) and unemployment-to-employment (UE) probabilities. This is just part of the story: the employment-to-inactivity channel is quantitatively important.[5]

As for older workers, our results imply that theories should be based on mechanisms explaining why it becomes increasingly less likely for them to re-enter the active labour force once they reach inactivity. For example, Hairault et al. (2010) show using a search and matching model that a finite horizon induces older workers to leave the labour force because the value of employment decays as they get closer to the final time period. However, our findings show that the re-entry decision is empirically more important: participation drops and unemployment remains stable for older workers because they stop searching for jobs once they become inactive.

Our study is related to a growing literature discussing the role of inactivity to understand labour markets.[6] The framework we present here naturally lends itself to studying how different versions of two-state models of the labour market (a common shortcut used in the literature) can replicate unemployment or employment profiles

[2] Many micro studies have confirmed that the labour supply elasticity is typically larger for workers at both ends of the life cycle (Blundell and Macurdy, 1999) and the macro literature has illustrated that employment volatility is larger for these demographic groups (Jaimovich and Siu, 2009).

[3] The approach in most of the literature is positive, see e.g. Kitao et al. (2008), Ljungqvist and Sargent (2008), Hairault et al. (2010), Esteban-Pretel and Fujimoto (2011), Menzio et al. (2012), with the exception of Chéron et al. (2011, 2013), Hairault et al. (2012a) and Michelacci and Ruffo (2010), who respectively analyse optimal employment protection and unemployment insurance over the life cycle.

[4] Esteban-Pretel and Fujimoto (2011) use random search and stochastic match quality; Menzio et al. (2012) develop a directed search framework with on-the-job human capital accumulation.

[5] Menzio et al. (2012) introduce exogenous labour force entry and exit to the labour force, but entry plays a role at the beginning of the life cycle and exit only at the end. Chéron et al. (2013) also generate a decreasing trend in the employment-to-unemployment probability at the beginning of the life cycle, but the focus of their paper is not quantitative.

[6] Examples of three-state models of the labour market are Alvarez and Veracierto (1999), Garibaldi and Wasmer (2005), Ravn (2008), Krussel et al. (2008), Veracierto (2008), Pries and Rogerson (2009), Krussel et al. (2010), Elsby et al. (2013), Shimer (2013) among others.

over the life cycle. More importantly, our decomposition exercises can give us an idea of the consequences of performing such simplifications. Section 4 shows that transition probabilities can replicate unemployment and employment rates over the life cycle quite well when inactivity is neglected but this result relies on a particular balance of worker flows, which is not tenable on theoretical grounds. Another approach, merging inactivity with unemployment into a single non-employment state, hides the behaviour of the unemployed, a group of particular interest. Our exercise also shows that three-state models should be preferred, given their generality and robustness. Furthermore, the distinction between unemployment and inactivity matters when individuals in those states are behaviourally different (as shown by Flinn and Heckman, 1983; Jones and Riddell, 1999, 2006 and our own findings) or if the model is ultimately used for counterfactuals, policy or welfare analysis.

Finally, Section 5 shows that our conclusions remain unchanged under several potential caveats including various methodological issues in our baseline method, time-aggregation bias, misclassification errors and several forms of heterogeneity.[7]

1. Data and Empirical Analysis

Our data source is the basic monthly data files from the CPS.[8] Our sample consists of individuals observed between January 1976 and April 2013. Throughout the study, we perform all analysis after separating male and female samples. In each month (period t), workers are employed (E), unemployed (U) or inactive/out-of-the-labour-force (O).[9] Figure 1 displays the evolution of unemployment and participation over the life cycle for the two gender groups.

We match individuals across consecutive months based on the interview identification number, gender, race and age.[10] The rotating panel structure of the CPS allows us to match individual records up to four consecutive months. Thus, we have longitudinal data to calculate flows between these three employment states for each month. We define indicator variables D_{nt}^{XZ} that take the value of 1 if individual n has transitioned from labour status $X \in \{E, U\ O\}$ in period $t-1$ to labour status $Z \in \{E, U, O\}$ in t (for expositional reasons, we ignore gender indicators). Then, we take averages of these indicator variables for each month t, for each age a and for each birth cohort c to obtain a measure of monthly, age and cohort specific transition probabilities between employment, unemployment and out of labour force states, using CPS weights. We denote $\mathbb{I}(a, t, c)$ as an indicator variable that takes the value of 1 if the individual is observed in month t, belongs to cohort c and is a years old, and 0 otherwise. Then, we define the corresponding worker flow f_{atc}^{XZ} as follows:

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[7] A more extended and in-depth analysis is explained in the online Appendix.

[8] Available from the National Bureau of Economic Research, at http://www.nber.org/data/cps_basic.html

[9] In what follows, we use subscript a to denote age of a variable.

[10] The unit of analysis in the CPS is a physical address hence the same identification number during two consecutive months might not correspond to the same person. Admittedly, the estimates we provide may be slightly biased since the relatively small sample of movers are qualitatively different from stayers. Other papers using this data set have the same shortcoming. We comment on this below.
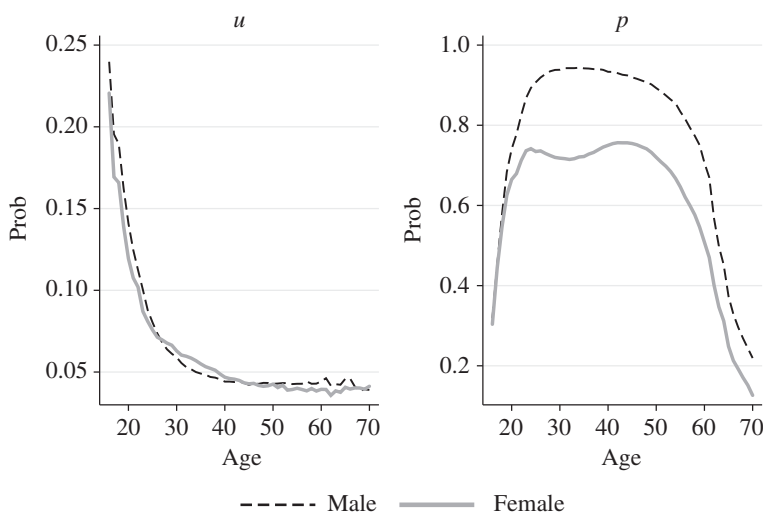
Fig. 1. *Life-cycle Unemployment and Participation Profiles*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

$$f_{atc}^{XZ} = \frac{\sum_{n=1}^{N} D_{nt}^{XZ} \times \omega_{nt} \mathbb{I}(a,t,c)}{\sum_{n=1}^{N} D_{nt}^{X} \times \omega_{nt} \mathbb{I}(a,t,c)},$$

where D_{nt}^{X} equals 1 if the individual was in state X in $t-1$ and ω_{nt} is the sample weight.

We obtain life-cycle profiles for each transition by running weighted[11] OLS regressions with our set of measured f_{atc}^{XZ} as our dependent variables and a set of age dummies as regressors without an intercept. Hence, the estimates are simply the weighted average frequencies of transitions by age. Throughout the study we refer to our OLS estimates simply by their associated transition. For example, the OLS estimate associated with a binary variable for age a is the 'EU_a' transition when the dependent variable is f^{EU}. Our baseline results are based on unconditional age-specific transition probabilities, because the results remain unchanged after several robustness exercises we explain in Section 5 and in the online Appendix, in greater detail.

We depict the unconditional estimated life-cycle profiles in Figures 2 and 3 in the case of the male and female population respectively. Since we are interested in the average transition probability, our linear regression model does not have an intercept. The shaded areas around the profiles are 95% confidence bounds constructed from the estimated standard deviations of the weighted OLS estimates. Besides level differences, the male and female profiles are quite similar. Qualitatively, for both genders the employment-to-unemployment (EU), employment-to-inactivity (EO) and the unemployment-to-inactivity (UO) transition probabilities have stable patterns between 30 and 60 years of age, while they show a negative slope at younger ages and

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[11] Since age-time-cohort bins have different sizes, we weight each transition by the square root of the sample size of the initial state. In this way, we equally weigh all individuals in the sample.
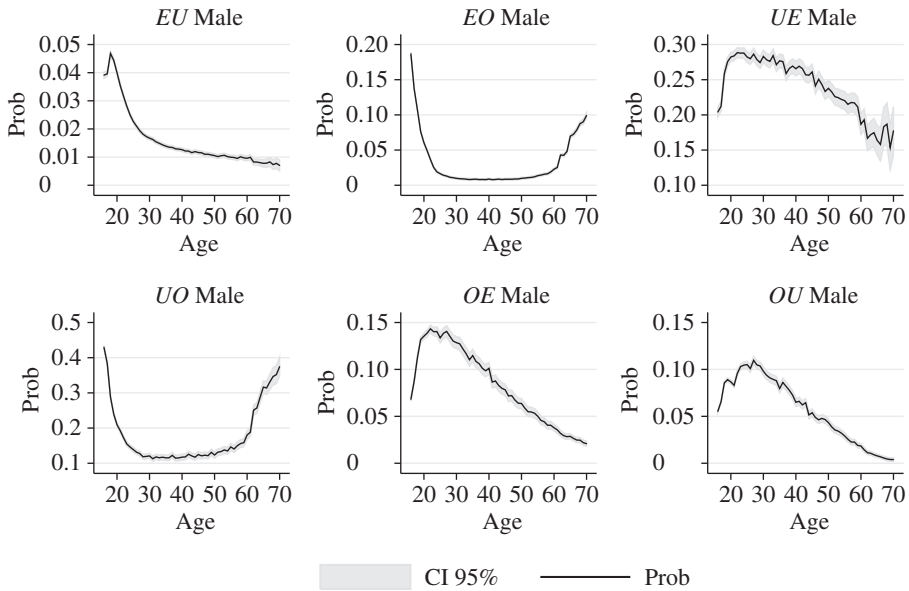
Fig. 2. *Life-cycle Profiles of Worker Flows Transitions: Males*
Note. Unconditional life-cycle profiles estimated via weighted OLS.
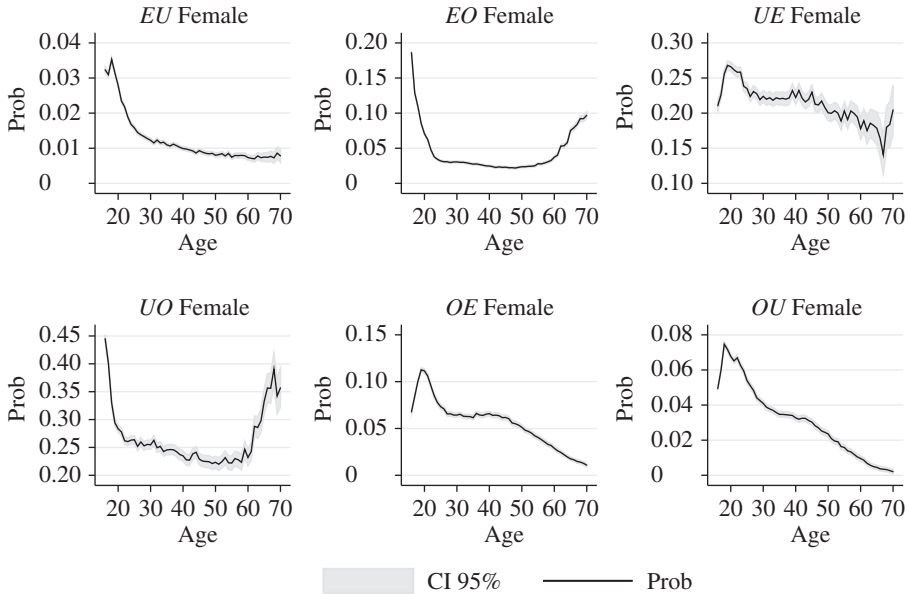

Fig. 3. *Life-cycle Profiles of Worker Flows Transitions: Females*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

an increase for older workers. The job finding probability (*UE*) shows an increase until the mid-20s and then a slight but persistent decrease. The probabilities of going from inactivity to both employment and unemployment (*OE* and *OU*) show hump-shaped

patterns, peaking in the mid-20s and steadily decreasing from that point to age 70. Confidence bands show that the estimated age profiles are precise, with the partial exception of *UE*.

As for other quantitative differences, the female sample exhibits a flatter profile of job finding probabilities and less pronounced hump-shaped patterns in *OE* and *OU*. The main differences are concentrated around ages 20–30, which are probably linked to fertility and child-rearing.

2. Markov Chain Analysis

In this Section, we propose a way to account for the contribution of each transition probability to the determination of participation ($p_a = 1 - O_a$) and unemployment ($u_a = U_a/(E_a + U_a)$) profiles over the life cycle. Once we get our estimates for transition probabilities, we construct age-specific Markov transition matrices denoted Γ_a. Starting from initial conditions on the distribution of workers among labour force statuses at some starting age S_1, we compute the predicted labour market states after 12 months as

$$S_2 = (\Gamma_1)^{12} S_1 \quad \text{with } \Gamma_1 = \begin{pmatrix} EE_1 & EU_1 & EO_1 \\ UE_1 & UU_1 & UO_1 \\ OE_1 & OU_1 & OO_1 \end{pmatrix} \quad \text{and } S_1 = \begin{pmatrix} E_1 \\ U_1 \\ O_1 \end{pmatrix}.$$

Using the same logic, we can obtain the distribution of workers among labour market states at any age a by doing the following calculation:

$$S_a = \left(\prod_{i=1}^{a-1} (\Gamma_i)^{12} \right) S_1. \tag{1}$$

Using (1), we can obtain complete lifetime profiles implied by the estimated transition probabilities, using observed initial conditions. We compare the computed lifetime sequences of participation and unemployment to the actual lifetime profiles obtained from the data. The results are depicted in Figure 4. The estimated transition probabilities come remarkably close to replicating the actual profiles. In each subfigure we also show the value of $1 - R^2$, where R^2 is the R-squared of a linear regression between the actual profile and the counterfactual.[12]

Looking at the female sample, participation exhibits a hump around ages 25–40, which can be linked to reduced participation due to fertility and child-rearing. Our method replicates this pattern, given the gender-specific estimates of *OE* and *OU*: these transition probabilities are lower for females than for males during these years, representing women's choices not to rejoin the labour force if not participating.

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[12] The dashed line in Figure 4 reports simulated unemployment and participation rates in the first month of a specific age category. An alternative would be to report the average unemployment and participation rates across all twelve months of the age category. In this case, the dashed line would be less shifted to the right with respect to the solid line.
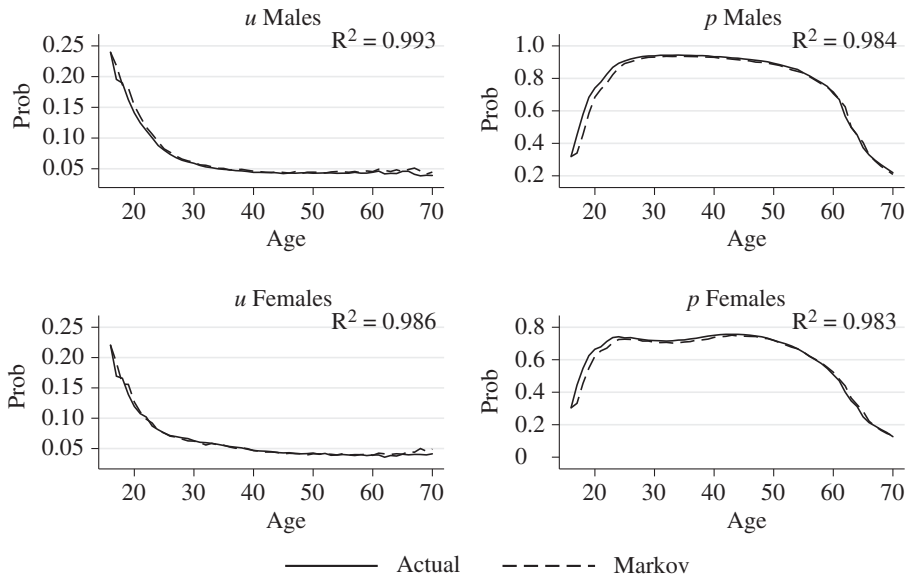
Fig. 4. *Markov-chain Simulated Unemployment and Participation*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

3. Results

3.1. *Methodology*

With the constructed transition matrices, we perform a set of decomposition exercises. The aim is to understand the importance of each labour-market transition probability for the observed differences in unemployment and participation between age groups. Thus, we fix the age-specific transition probability of each flow (*EU, EO, UE, UO, OE, OU*) to its average over the life cycle. Then, we adjust the probability of the 'staying' flows (*EE, UU, OO*) so that the monthly transition matrices are well defined.[13] The remaining five independent transition probabilities are left unchanged. Using this alternative set of age-specific transition matrices, we can assess the contribution of a specific flow by inspecting the loss of goodness of fit derived from such a change. We call this method 'all but one change' (AB1C). Figures 5–8 depict the alternative unemployment and participation profiles for both male and female workers. For example, the first subfigure in Figure 5 shows hypothetical life-cycle unemployment rates if the separation rate (*EU*) was fixed at the life-cycle average for all ages, instead of being age-specific. Hence, whenever there is a significant difference between the two lines, the particular transition probability contributes to the shape of the life-cycle profile in either participation or unemployment rates.

Looking at Figures 5 and 6, we observe that the implied unemployment profiles are barely affected by changes in the job finding (*UE*) and the inactivity-to-employment

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[13] Suppose we fix $EU_a = \overline{EU}$ for all a. We then adjust the transition matrices for all ages by computing $\widetilde{EE}_a = 1 - \overline{EU} - \overline{EO}_a$.
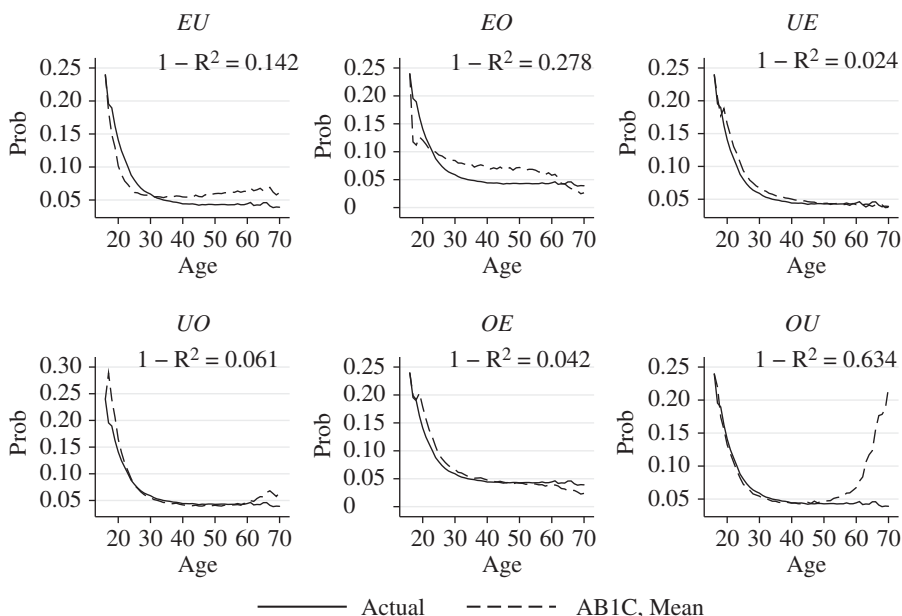
Fig. 5. *AB1C Decomposition of the Importance of Flows: Unemployment, Males*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

Fig. 6. *AB1C Decomposition of the Importance of Flows: Unemployment, Females*
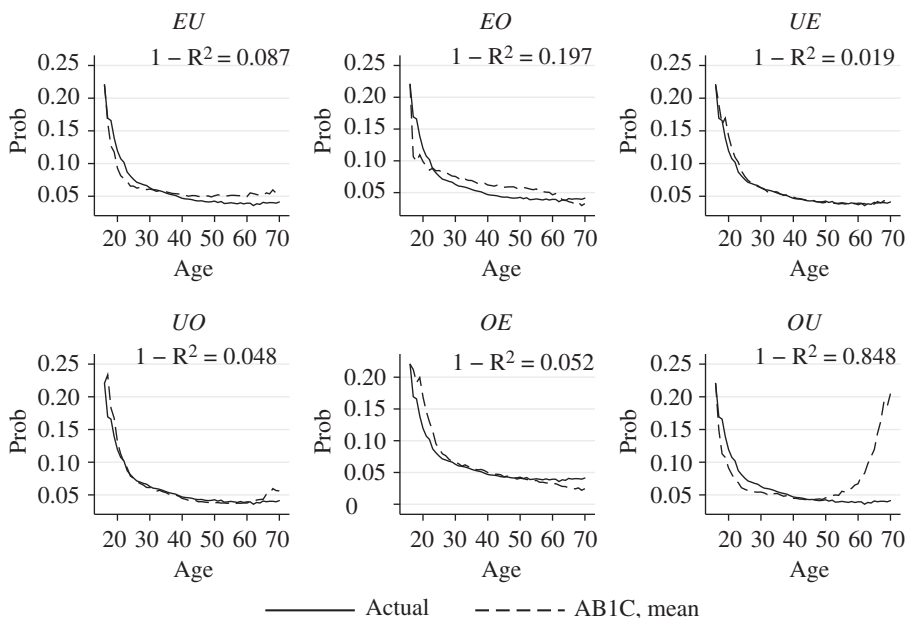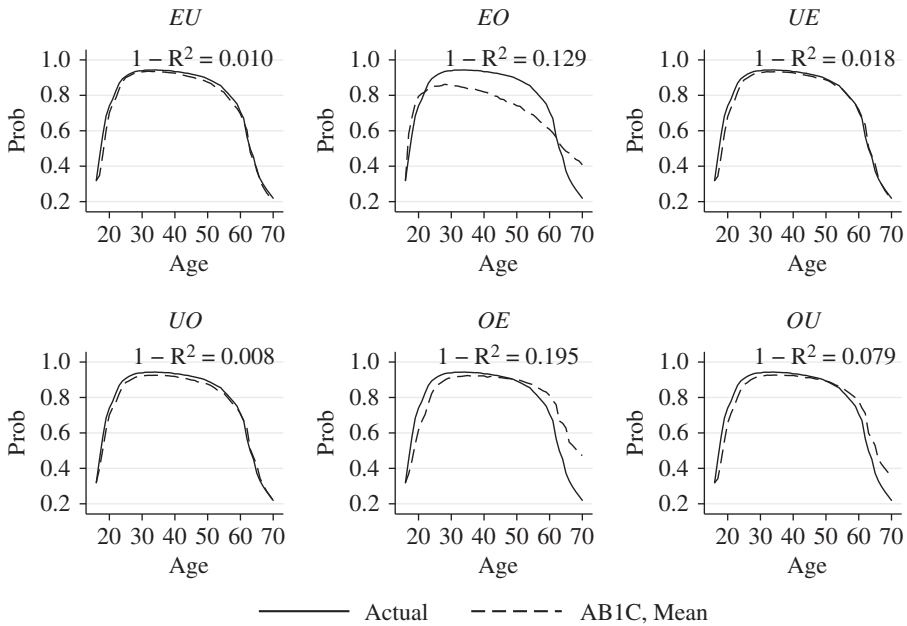*Note.* Unconditional life-cycle profiles estimated via weighted OLS.

Fig. 7. *AB1C Decomposition of the Importance of Flows: Participation, Males*
Note. Unconditional life-cycle profiles estimated via weighted OLS.
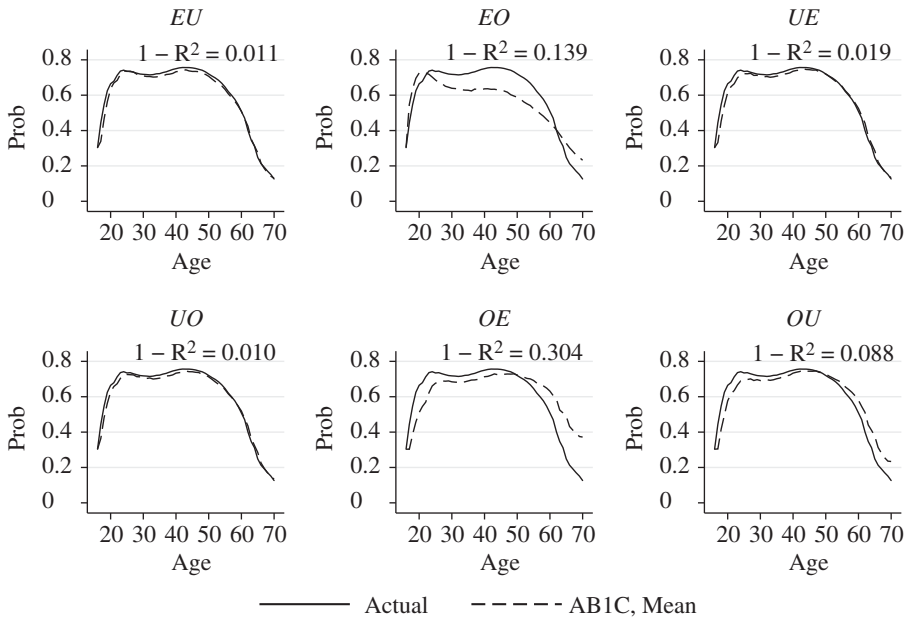

Fig. 8. *AB1C Decomposition of the Importance of Flows: Participation, Females*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

transition (*OE*) probabilities. Changes in the employment exit probabilities *EU* and *EO* matter in explaining higher unemployment among the young and the lower unemployment of older workers. Moreover, the probability of transiting from inactivity to unemployment is the most important factor in explaining low unemployment rates for workers older than 55 years of age. The importance and qualitative effect of each specific transition rate are similar for male and female unemployment.

Figures 7 and 8 show the decomposition for the participation rate. The pictures show that neither separation (*EU*), unemployment-to-inactivity (*UO*) nor job finding probabilities (*UE*) explain much of the age differences in participation rates. If these probabilities were fixed at their average life-cycle levels, we would observe a somehow lower participation for workers older than 40. The most important life-cycle changes that influence participation profiles come from the *OE* and *EO* transitions. Fixing these transition probabilities at their life-cycle averages, respectively, increases labour force participation by as much as 30% and 20% respectively at age 60.

In a nutshell, the levels of participation and unemployment of older workers are mainly due to their low probability of re-entering the labour force (exiting *O*), while the exit margin of employment is important for the population below age 30.

An alternative view of the facts is through the lens of prime-aged workers (30–50 years of age): both unemployment and participation are mostly affected by the *EO* transition for this group. Unemployment would be higher for them and participation lower if the *EO* transition was at its life-cycle average. This is due, mechanically, to the fact that the *EO* profile exhibits the widest range of values over the life cycle (thus, the biggest differences between what prime-aged workers and the rest experience): setting *EO* at its mean for the counterfactual analysis makes the simulated prime-age individuals go through unemployment and non-participation much more frequently than their observed counterparts. This does not happen with other flows, which are more stable during the life cycle. Intuitively, this is reflecting the fact that prime age workers are more attached to the labour market than the rest of workers and less prone to leave employment for inactivity.

3.2. *Interpretation*

Our results present a range of facts that could serve as guidelines for researchers who work on life-cycle models of unemployment and labour force participation. Specifically, they help identify which flows should be carefully modelled in order to reproduce the observed evolution of unemployment and participation over the life cycle. Hence, when building these models, introducing mechanisms that decrease the probability of re-entering the labour force at the end of the life-cycle and increase probabilities of exiting employment at the beginning of the life cycle should be priorities. At first glance, these mechanisms should consider inactivity as a relevant alternative to employment and unemployment for both younger and older workers. For example, it may be tempting to acquire more education for young individuals if they lose their jobs; older workers may have incentives to enjoy (or be forced into) retirement sooner when labour market conditions are not good. For prime-aged workers on the other hand, wealth accumulation for retirement or for consumption smoothing might play a significant role for their high participation rates.

In a life-cycle context, it seems a natural result that transitions to and from inactivity matter for the evolution of unemployment and participation. An interesting aspect of our results is that the margins that drive the observed differences are not the ones that one would expect *a priori*: the change in the exit margin matters for the young population, while the change in the entry margin is relevant for older workers.

There are several mechanisms that may be consistent with a decrease in the relative importance of the exit margin observed at the beginning of the life cycle. The Mincerian approach assumes that human capital can be accumulated through labour market experience. With experience, the productivity of young workers would increase with age, reducing the likelihood of a job separation and the sensitivity of the exit margin to age. Theories based on mismatch (such as Burdett, 1978, who suggests that the positive correlation between labour market experience and wages may be a simple consequence of the fact that it takes time for young workers to find an appropriate job) would produce similar effects: the exit margin would become less sensitive once the 'correct' job has been found. Menzio *et al.* (2012) suggest that this dimension helps generate higher separation among young workers.

Other mechanisms may yield a lower probability of entering the labour force for the older population. A first possibility is the fact that this demographic group may choose to retire sooner because of a finite horizon effect produced by the official retirement age: because of the presence of search and matching frictions in the labour market, older workers may not be willing to pay a search cost to find a job that will not last long. Hairault *et al.* (2010) propose a similar mechanism to explain differences between OECD countries in the employment rates of older workers. In their model, early exit occurs because older workers move from employment directly to inactivity at a faster pace. Our results suggest that early exit may rather occur in the stage of non-employment.[14] We can imagine that extending the framework of Hairault *et al.* (2010) to include inactivity could produce a lower probability of entering the labour force for the older population. Second, the strong depreciation of older workers' human capital stock may also be behind this pattern. The incentives to search for a job would be significantly reduced after depreciation. Ljungqvist and Sargent (1998, 2008) suggest that this may explain the low employment level in Continental Europe. Finally, the high stock of accumulated savings of older worker may also have an effect because this might reduce the incentive to search for a job when older through a standard wealth effect, as suggested for instance by Lentz and Tranaes (2005).

All these mechanisms are consistent with the facts we illustrate in this article. Notice, however, that our results do not necessarily justify the use of three-state models over models that only include two states. Indeed, even though transitions towards inactivity may be quantitatively important in the data, how we interpret the observed lifetime differences in labour market outcomes and, more importantly, what type of policy recommendations arise from the exercise, depend on the theoretical model at hand: we still need to understand the importance of pull and push factors separately. For

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[14] Coile and Levine (2007) and Hairault *et al.* (2012*b*) provide evidence that labour market conditions may induce older workers to retire earlier. Our results suggest that this fact may be the reason why the unemployment rate of older workers is similar to prime-aged workers.

example, if it is very likely for young employees to move towards inactivity, it is not clear whether this is due to frequent lay-offs that are pushing young workers towards education or whether this is because young workers value education more than the rest of the population, pulling these workers out of the labour market. In the former situation, a model encompassing unemployment and inactivity into a single state should be enough to describe the behaviour of young workers, while the distinction between unemployment and inactivity is necessary in the latter.

Similarly, if matching frictions explain the lack of incentive to search for a job in the case of older workers, this can be modelled with only two states. On the other hand, if we are interested in how individuals use different welfare programmes later in life (unemployment *versus* disability insurance or early retirement, for example), the unemployment/inactivity distinction becomes important again.

3.3. *Further Analysis*

Alternative explanations for our results might be based on heterogeneity of observable characteristics. For example, the importance of the employment exit margin among young workers could be due to the fact that these individuals have not yet gone to college or family/demographic characteristics (dependants for example) that affect their ability to commit to work. One could also argue that there are important time effects we have neglected and that might have non-trivial effects on different age groups.

Below, we explore the generality of our approach by dissecting the data in several ways. First, we separately analyse individuals with different educational attainment. Then, we analyse whether household composition affects our conclusions. A third exercise interacts the life cycle with the business cycle, by analysing which transitions appear important for the increase in unemployment during the great recession sample (sample post-January 2007). We find that the main conclusions of the previous subsection remain, even when we analyse very different samples.

3.3.1. *Analysing educational groups*

The first application extends our results to different educational groups. Figure 9 shows the results of the unemployment decomposition exercise in the case of workers who do not hold a college degree and Figure 10 considers individuals with a college degree. The two groups of workers face very distinct unemployment profiles along the life cycle. The unemployment rate of non-college workers is higher for any age category. This is mainly due to the higher separation probability of this population group, confirming well-known evidence on the higher turnover rate of the unskilled (Hamermesh, 1993). Moreover, while the unemployment rate of non-college workers is decreasing over the life cycle, the one of workers holding a college degree follows a U-shaped pattern. This may explain why unemployment is barely flat over the life cycle after a certain age for the entire population, as seen in Figure 4.

Interestingly, although the two education groups have different characteristics, it seems that the same message comes out of this exercise: changes in the employment exit margin matter for young unemployment, while changes in the labour force entry margin explain the behaviour of older workers. In these graphs, the exit margin
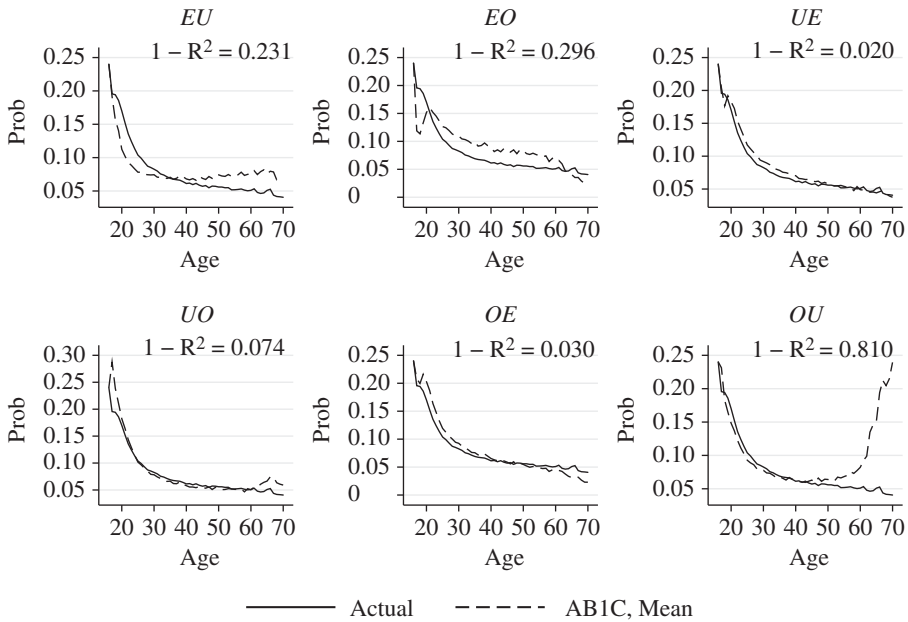
Fig. 9. *AB1C Decomposition of the Importance of Flows: Unemployment, Males, Non-college*
Note. Unconditional life-cycle profiles estimated via weighted OLS.
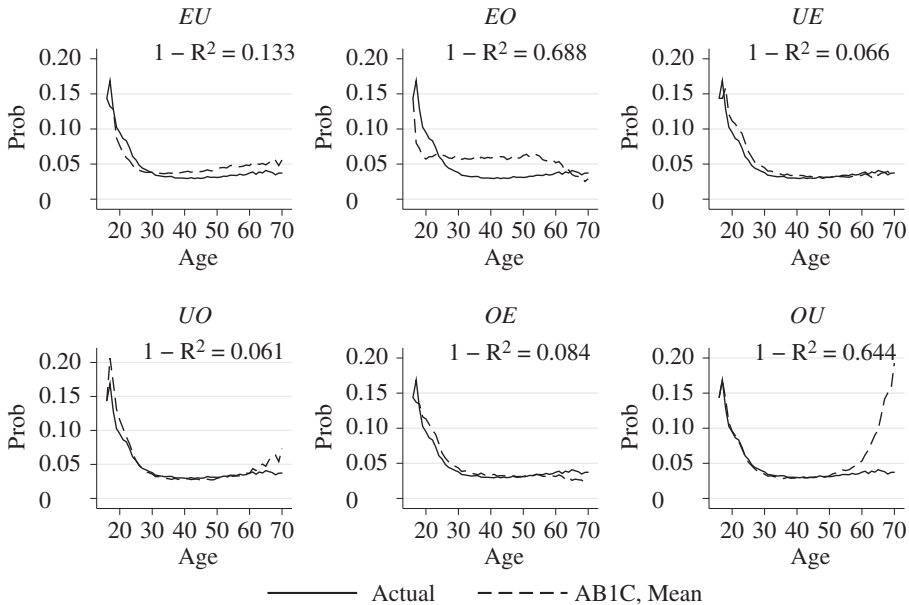

Fig. 10. *AB1C Decomposition of the Importance of Flows: Unemployment, Males, College*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

appears to contribute a bit more to the level of unemployment among the older population but it turns out that the importance of the entry margin is even more significant. For females of different educational attainment, the story is similar, thus we omit it from the main text. Further details of this analysis are in the online Appendix, Section A.

3.3.2. *Analysing family factors*

Family factors drive much of life-cycle behaviour, particularly for females. We apply our method to different segments of the labour market, according to child presence and marital status. We report the relative importance of transition probabilities according to the AB1C method for the unemployment profiles of females with and without a child at home. The first stark result in Figures 11 and 12 is that females with no child quickly converge to their prime-aged unemployment rates, while their counterparts reach such a level around age 40. Labour market and fertility histories are noticeably related over the life cycle. Several reasons may be behind the higher unemployment rate of young women with children, such as delayed human capital accumulation (Mincer and Polachek, 1974), the need to financially support their family or a higher outside option in wage negotiation.

Despite the large discrepancies of these two groups, the AB1C decomposition shows that the qualitative conclusions for the baseline exercise remain intact. The *OU* flow is the most important driver of unemployment over age 50. For females with a child, it also matters below age 30. Besides the latter, the *EU* and *EO* flows still matter for both groups over the whole life cycle. In both cases, the job finding probability, *UE*, has little
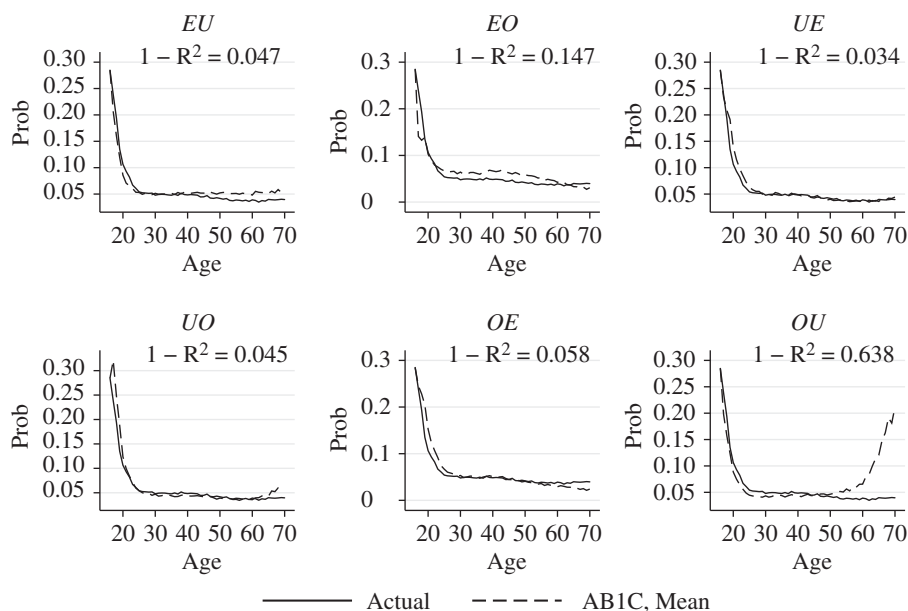

Fig. 11. *AB1C Decomposition of the Importance of Flows: Unemployment, Females, No Child*
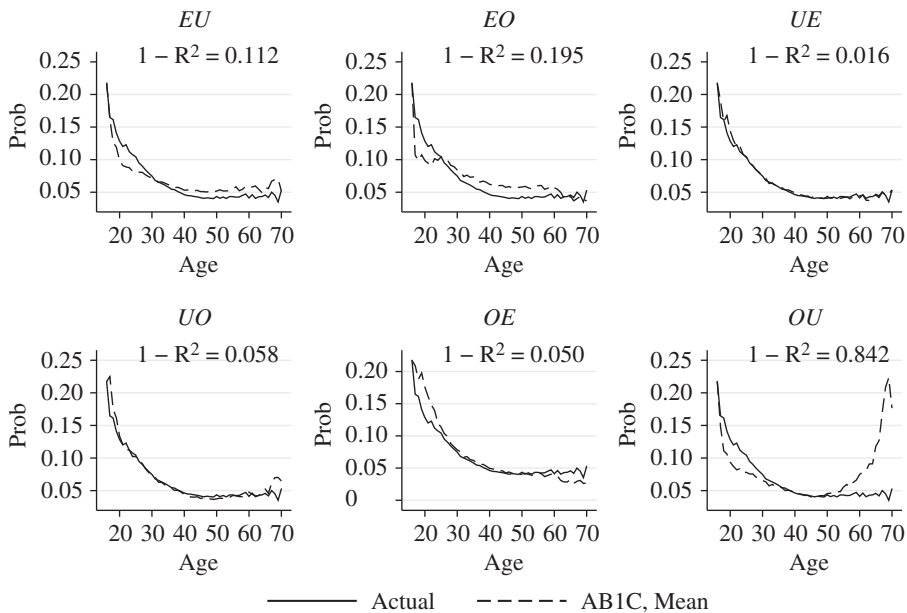*Note.* Unconditional life-cycle profiles estimated via weighted OLS.

Fig. 12. *AB1C Decomposition of the Importance of Flows: Unemployment, Females, with Children*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

importance. When we segment the labour market according to marital status, we reach to the same ranking of relative importance of flows in shaping unemployment and participation profiles. A detailed analysis of these results is shown in the online Appendix, Section A. These exercises suggest that the underlying mechanisms behind life-cycle profiles are the same even for groups showing very different behaviour over the life cycle.

3.3.3. *Impact of the great recession*

In this application, we compare labour market outcomes during the Great Recession with those observed before this episode. Figure 13 displays unemployment and participation rates as a function of age for two periods (before and after 2007), in the case of male workers. As expected, the figure shows that unemployment is higher for all age categories after 2007. Youth unemployment seems to be particularly affected by the recession. Youth participation is also negatively affected. Interestingly, participation among older workers is higher for the post-2007 sample, though it is not clear whether this was caused by a wealth effect provoked by the financial crisis that induced older individuals to participate more or by an idiosyncratic characteristic of this specific cohort. In any case, the Figure shows that youth is the demographic group that has been most affected by the recession, confirming evidence in Elsby *et al.* (2010).

In Figure 14, we perform the following exercise in order to identify which labour market transitions generate the differences in unemployment between the two periods. The solid line represents the difference in unemployment rates that is observed in the data, while the dashed line shows what this difference would have been if all transition
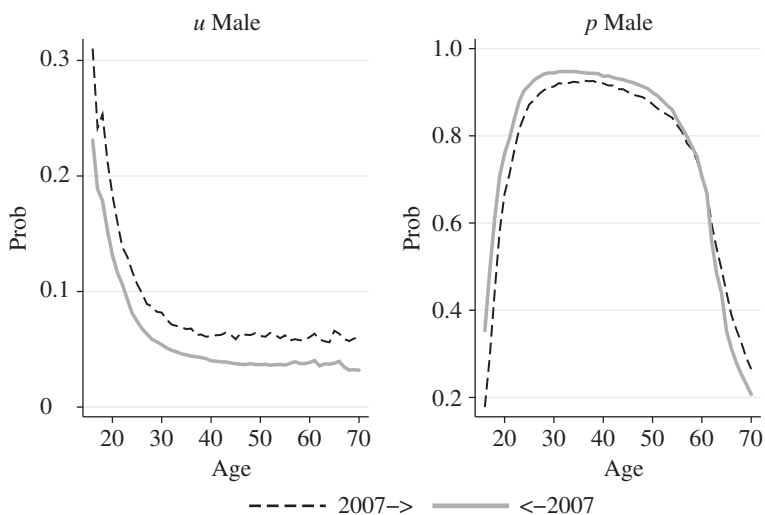
Fig. 13. *Unemployment and Participation: Pre-2007 Versus Post-2007*
Note. Unconditional life-cycle profiles estimated via weighted OLS.
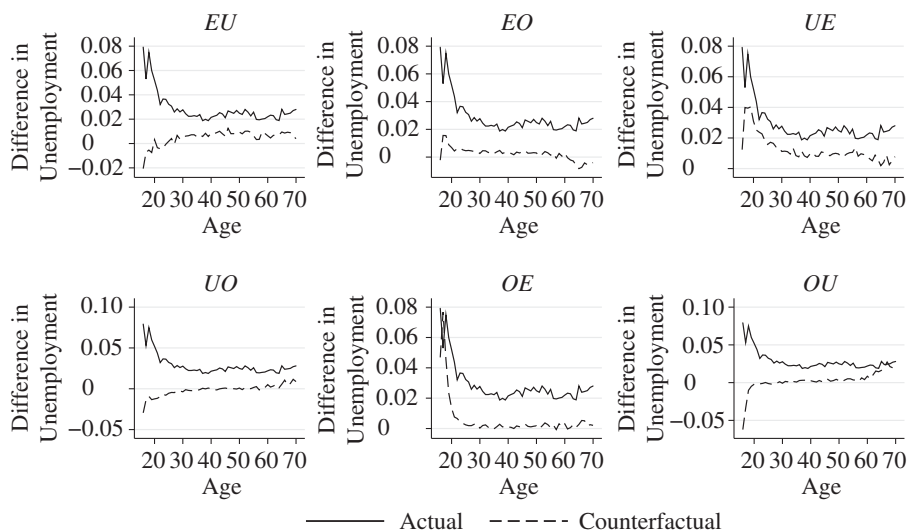
Fig. 14. *AB1C Decomposition of the Importance of Flows: Change in Unemployment*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

probabilities had remained invariant between the two periods except for one. For example, in the first panel of the Figure, the dashed line shows the difference in unemployment if only the EU transition probabilities had changed between the two periods, while the remaining transition probabilities had remained fixed at their pre-2007 levels. Hence, we interpret a transition probability as important in generating the difference in unemployment between the two periods when the dashed line is close to the solid line.

Interestingly, the Figure confirms findings from the business cycle literature in the sense that the hiring margin is key in explaining the behaviour of unemployment during the recession period. However, it seems that this only explains the labour market outcomes of young workers (and prime-aged to some extent): the UE and OE transitions reproduce a large share of the difference in unemployment for young workers. Differences in unemployment among older workers are mainly due to the OU transitions. Hence, older workers seem to be more attached to the labour market in the post-2007 sample. Once again, it is not clear whether a wealth effect explains this higher labour market attachment or whether it is a characteristic of this specific cohort but the exercise in Figure 14 shows that the labour force entry margin, which is important in explaining the unemployment of older workers in Figure 5, also appears key in the context of the post-2007 period. We provide further analysis in the Section B of the online Appendix.

4. The Role of Inactivity

In this Section, we consider two common approaches for dealing with inactivity in labour markets. First, as in the search and matching models of the Mortensen and Pissarides (1994) tradition, we abstract completely from inactivity and solely focus on job finding and job separation probabilities. Second, we merge unemployment and inactivity into a non-employment state. The blurred line between unemployment and inactivity is often used to justify this idea. Since flows to and from inactivity are sizeable, they might indicate search activity by individuals in the O state (see Yashiv, 2006), casting doubt on whether individuals in that state are really not looking for work.

4.1. *Abstracting from Inactivity or EU and UE Transitions*

What happens if we abstract from inactivity? To answer this question we extend the decompositions of Section 3 in several directions. First, we abstract completely from inactivity by setting all transition probabilities equal to zero, with the exception of the *UE* and *EU* transitions. Using the Markov chains as in previous Sections, we then recalculate the unemployment rate over the life cycle and compare it with the actual data. The southeast panels of Figures 15 and 16 do this comparison in the case of male and female workers respectively. Surprisingly, the fit of the counterfactual exercises turns out to be nearly perfect. The southwest panels of the Figures illustrate a similar exercise, where all transition probabilities are set to their life-cycle averages, with the exception of the *UE* and *EU* transitions. We label these procedures as AB2F, or 'all but two fixed'. These results suggest that transitions to and from inactivity are unimportant in explaining the evolution of unemployment over the life cycle, which seem at odds with the results from Section 3.

   To delve deeper into this problem, we also consider the reverse exercise. We abstract from transitions between unemployment and employment and leave space only for transitions to and from inactivity. We do this by fixing the *UE* and *EU* transition probabilities at arbitrary values, while letting all remaining transition probabilities behave as in the data. We label these decompositions as 'all but two change' (AB2C). The upper panels of Figures 15 and 16 illustrate the results of these exercises. In the

Fig. 15. *AB2 Decomposition Neglecting Inactivity for Life-cycle Unemployment Rates, Males*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

Fig. 16. *AB2 Decomposition Neglecting Inactivity for Life-cycle Unemployment Rates, Females*
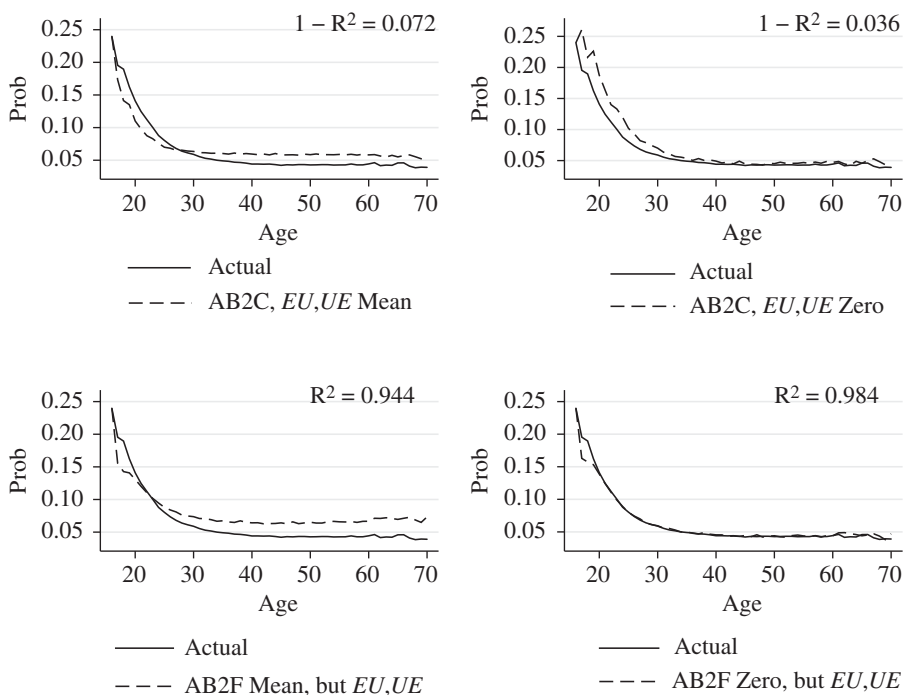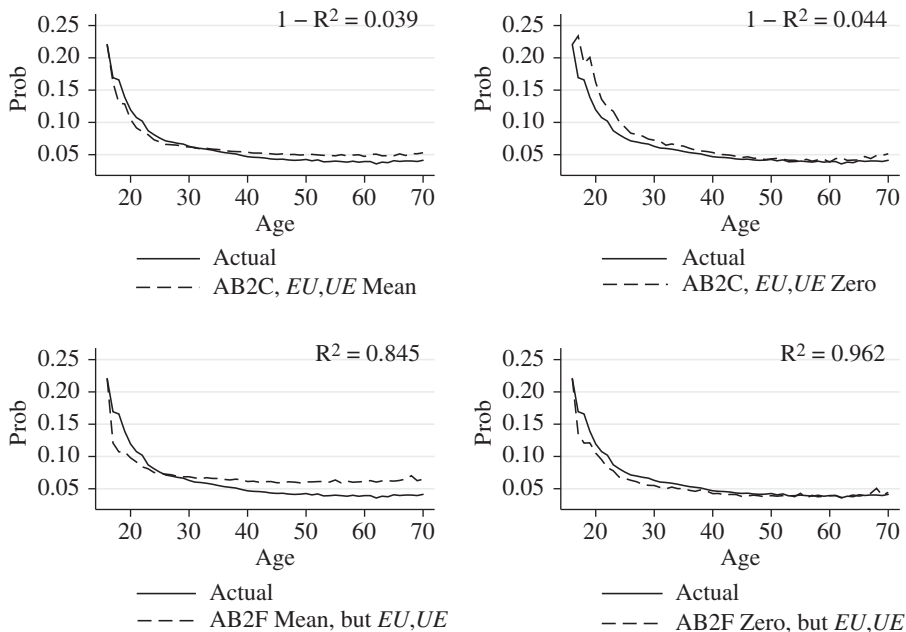*Note.* Unconditional life-cycle profiles estimated via weighted OLS.

northeast panels, *UE* and *EU* take value zero for any age group, while they are fixed to their life-cycle average in the northwest panels. By comparing the actual unemployment evolution over the life cycle to the counterfactual profiles obtained by our AB2C method, transitions between unemployment and employment seem unimportant. Hence, results from AB2F and AB2C exercises seem contradictory. What produces these results?

To explain these findings, we use the approximation used in Shimer (2012) and calculate under which condition two and three-state models generate the same unemployment rate. This exercise also allows us to understand when a policy change may affect unemployment differently in both models.

Let $\tilde{u}_a$ be an approximation to the unemployment rate in terms of transition probabilities (for further details, see the online Appendix D)

$$u_a \approx \tilde{u}_a = \frac{OE_a EU_a + OU_a(EU_a + EO_a)}{OE_a(UO_a + EU_a) + UE_a(OE_a + OU_a) + OU_a(EU_a + EO_a)} \tag{2}$$

$$= \frac{EU_a + A_a}{EU_a + UE_a + B_a} \tag{3}$$

$$\text{with } A_a \equiv \frac{EO_a OU_a}{OE_a + OU_a} \text{ and } B_a \equiv \frac{EO_a OU_a + UO_a OE_a}{OE_a + OU_a}. \tag{4}$$

Expression (3) resembles the standard steady-state unemployment obtained in a two-state labour market $EU_a/(EU_a + UE_a)$.[15] It can be shown that unemployment rates in two and three-state models are similar if

$$\frac{EU_a}{EU_a + UE_a} \approx \frac{EO_a OU_a}{EO_a OU_a + UO_a OE_a} = \frac{A_a}{B_a}. \tag{5}$$

This equation tells us that both approximations are quantitatively similar if the ratio of flows from employment to unemployment through inactivity (*EO–OU*) to the flows from unemployment to employment through inactivity (*UO–OE*) is similar to the ratio of 'direct flows' between *EU* and *UE*. Intuitively, this is an 'inactivity irrelevance condition', because whether workers make an inactivity transition or not does not influence the unemployment rate. Figure 17 plots the left and right-hand sides of (5) and shows that their magnitudes are similar over the life cycle, especially for males. This explains the good fit of the simulations of both upper and lower panels in Figures 15 and 16.

Given this discussion, the two-state labour market simplification is useful if the 'inactivity irrelevance condition' holds. However, we do not have theoretical reasons supporting this condition (5). If we use a two-state model, it is hard to anticipate whether this condition (5) would hold after a policy change.

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[15] This expression converges to the two-state labour market unemployment rate as all inactivity-related flows approach to zero.
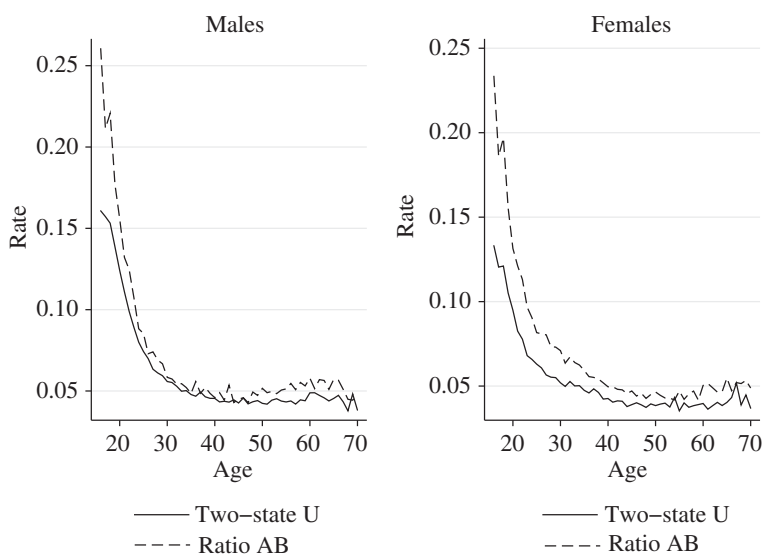
Fig. 17. *Condition for a Two-state Model to Fit the Unemployment*
Note. 'Two-state U' reports the left-hand side of (5), while 'ratio A/B' is the right-hand side of the same approximation.

4.2. *Merging Unemployment and Inactivity*

Instead of ignoring inactivity, an alternative procedure is to merge individuals who are out of the labour force with those unemployed, leading to a two-state setup with employment (E) and non-employment (N) as the only two labour market states. Some authors advocate this view, such as Blanchard and Diamond (1990) and Andolfatto and Gomme (1998), as they question the traditional three-state setup due to the large gross flows between inactivity and employment.[16]

We compute the *EN* and *NE* transition probabilities from the CPS data, in a similar fashion as in our main exercise. We perform the same Markov chain analysis and replicate the employment-to-population rate, as shown by Figure 18 (unemployment is obviously not defined here). Unsurprisingly, the employment rate behaves much like the participation rate because the number of unemployed workers is small in comparison to the number of employed or inactive workers.

Next, we perform an AB1C decomposition of the *EN* and *NE* flows to assess their contributions in shaping the employment rate. Fixed probabilities are set at their life-cycle mean, as before. The results in Figures 19 and 20 are similar to the participation results of Figures 7 and 8. They show that both transition probabilities are important in explaining the employment profile, with entry being more important, especially in the case of older workers.

By merging unemployment and inactivity into a single state, transitions from employment to non-employment (*EN*) are technically a mixture of transitions *EU* and

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[16] Yashiv (2006) adopts an agnostic view regarding the relevant measurement of theoretical variables in search and matching models.
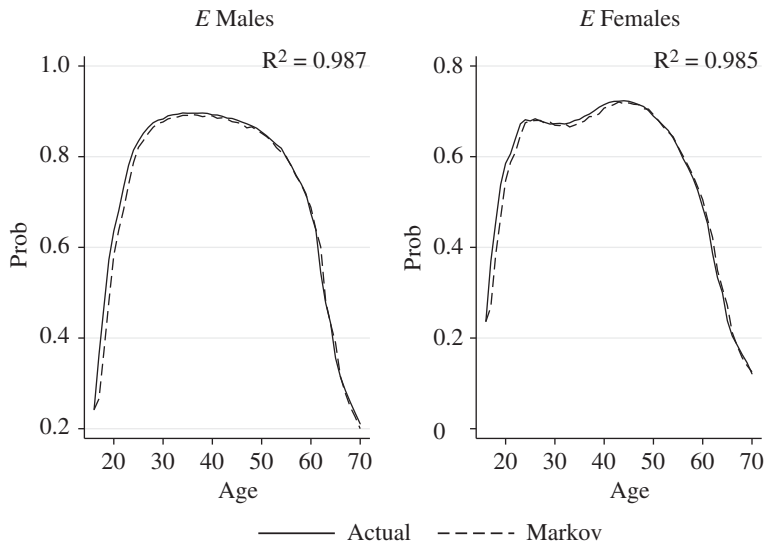
Fig. 18. *Markov-chain Simulated Employment-to-Population*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

Fig. 19. *Markov-chain Simulated Unemployment and Participation, Two States, Males*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

EO. Similarly, the transition into employment (*NE*) is a weighted average of *UE* and *OE*. By inspecting Figures 7 and 8 (our baseline AB1C decomposition for participation), we see that both *EU* and *UE* play negligible roles for participation rates. At the same time, the effects of *EN* and *NE* in Figures 19 and 20 mimic almost one-to-one the effects of *EO* and *OE* in Figures 7 and 8. This implies that life-cycle variation in the employment rate
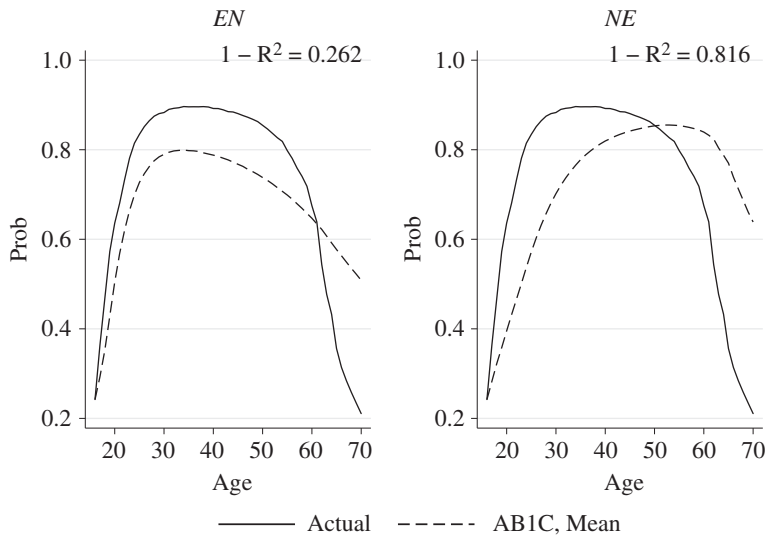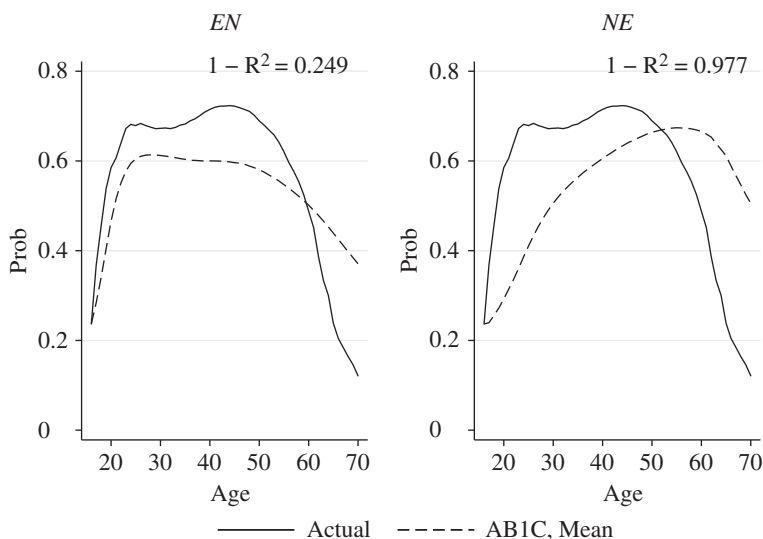
Fig. 20. *Markov-chain Simulated Unemployment and Participation, Two States, Females*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

is mainly due to *EO* and *OE* flows. Therefore, the merging approach is simply not informative about the behaviour of the unemployed at different stages of the life cycle, usually an important concern for researchers and policy makers.

4.3. *Focusing on the Prime-aged*

In the light of our previous results, it is natural to ask if a researcher could abstract from inactivity-related flows if interested only in prime-aged workers, the most relevant group of the workforce. To answer this concern, we restrict our study to individuals of ages 30–50. Starting from age 30, we investigate the impact of each transition probability using the AB1C method. The results are shown in Figures 21 and 22. A more detailed analysis is in the Section C of the online Appendix. Unsurprisingly, the importance of transitions to and from inactivity is toned down for this group but their effects do not disappear. For males, the most important flow driving the unemployment rate between ages 30 and 50 is *EU* but *OU* is still relevant, particularly for those in the range 40–50. For females, however, the flow *OU* is still the most important one using the goodness-of-fit metric and the *EU* transition is a close second. While the importance of inactivity flows matters more at the extremes of the life cycle, researchers should pay attention to them even for prime-aged workers.

In sum, inactivity is a key consideration for labour markets over the life cycle. While the alternative approaches of 'neglecting' or 'merging' inactivity may be useful in some contexts, a three-state framework is our preferred setup. The latter is certainly recommendable when the researcher builds a model for studying counterfactuals, a major concern from a public policy perspective. Neglecting inactivity imposes the 'inactivity irrelevance condition' described above in an unwarranted and *ad hoc*

Fig. 21. *AB1C Decomposition of the Importance of Flows: Unemployment, Males, Age 30–50*
Note. Unconditional life-cycle profiles estimated via weighted OLS.

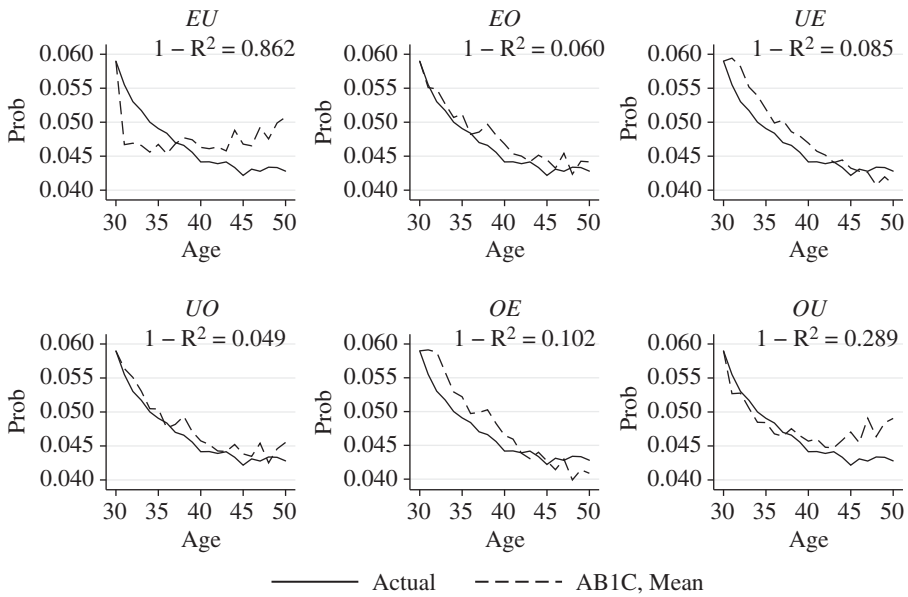Fig. 22. *AB1C Decomposition of the Importance of Flows: Unemployment, Females, Age 30–50*
Note. Unconditional life-cycle profiles estimated via weighted OLS.
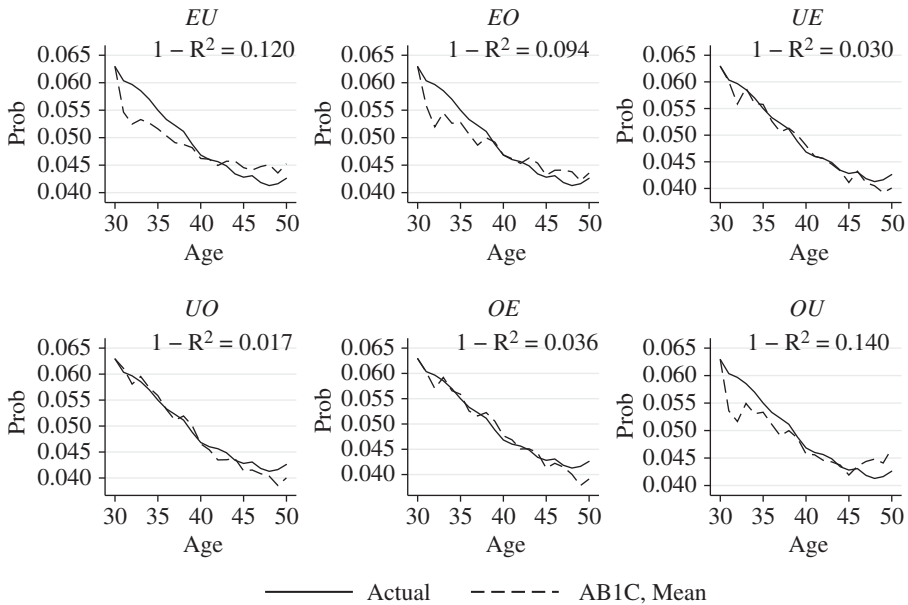
fashion, since this condition might be broken by the policy change under consideration. The three-state approach is also preferable in a context where we need to distinguish unemployment behaviour by itself, something that is clearly missing in a

'merging' perspective. Joining U and O can be a reasonable shortcut for studying employment or the extensive margin of labour supply over the life cycle but hides the flow of the most active job seekers, a group of high interest. While the importance of inactivity-related flows is remarkable for younger and older workers, we show it is also a relevant force for the prime-aged, with the partial exception of males in their thirties. Although in some cases parsimony considerations lead to some form of two-state models, researchers should keep in mind that the unemployed and inactive workers are behaviourally different on average (Flinn and Heckman, 1983; Jones and Riddell, 1999) and over the life cycle, as shown in previous sections.

5. Robustness

In this Section, we study the robustness of our conclusions to several potential issues.

5.1. *Alternative Decomposition Methods*

Our decomposition method yields similar results to that in Pissarides (1986) and Shimer (2012). Basically, these authors obtain approximations to the unemployment and labour force participation rates as the limit of the Markov chain of probability transitions. Our results are quite similar because iterating a Markov chain twelve times with high off-diagonal probabilities rapidly converges to its limit. In the online Appendix, in Section D, we provide further discussions and results for the AB1C decomposition using this method, but our results barely change.

5.2. *Alternative Age Decompositions*

Admittedly, the choice of keeping each transition probability fixed at its average life-cycle value is arbitrary. For example, we could focus on what would be the unemployment or participation life-cycle profiles if workers had the job finding probability of a 20 year old worker (*UE* transition) instead of the lifetime average. We answer this question by using the AB1C decomposition with the probability of interest fixed at arbitrary ages. We focus on young (20), prime age (40) and older (60) workers.

Table 1 summarises the results from this decomposition exercise as well as the average probability case shown in Figures 5–8. Using the AB1C method, we compute the loss of goodness of fit as $1 - R_{xz}^2$, where the last term is the R-squared of a regression between the actual life-cycle profile of unemployment/participation and the one simulated via an adjusted Markov chain with the probability transition *XZ* fixed at the specified age.

From Table 1 we see that the *EO* and *OU* flows are the most influential ones in determining the life-cycle trajectories of unemployment. For instance, if a worker keeps his *EO* transition probability fixed at its 20-year level, the Markov chain analysis would explain 85% less than what it could if we allowed age dependent *EO* values. Once we fix the *EO* probability at other ages, this number decreases to 20%. Thus, the *EO* flow is particularly important in determining unemployment for young male workers. In contrast, the *OU* flow plays an important role in shaping unemployment at all ages.

Table 1

Unemployment and Participation: Alternative Flow Decompositions by Age

	EU	EO	UE	UO	OE	OU
Males						
U, mean	0.142	0.278	0.024	0.061	0.042	0.634
U, age 20	0.206	0.429	0.015	0.052	0.052	0.678
U, age 40	0.139	0.192	0.018	0.086	0.043	0.652
U, age 60	0.137	0.239	0.047	0.061	0.065	0.389
P, mean	0.010	0.129	0.018	0.008	0.195	0.079
P, age 20	0.012	0.193	0.018	0.009	0.276	0.103
P, age 40	0.010	0.207	0.018	0.007	0.226	0.085
P, age 60	0.011	0.118	0.018	0.008	0.115	0.050
Females						
U, mean	0.087	0.197	0.019	0.048	0.052	0.848
U, age 20	0.085	0.259	0.013	0.044	0.026	0.895
U, age 40	0.088	0.174	0.017	0.055	0.040	0.854
U, age 60	0.090	0.186	0.028	0.056	0.106	0.593
P, mean	0.011	0.139	0.019	0.010	0.304	0.088
P, age 20	0.009	0.200	0.019	0.010	0.458	0.147
P, age 40	0.012	0.100	0.019	0.009	0.342	0.091
P, age 60	0.013	0.121	0.019	0.009	0.174	0.056

Notes. The numbers represent the loss of goodness of fit measured by $1 - R_{XZ}^2$, where R^2 is the R-squared from a regression between the actual life-cycle profile of unemployment/participation and the one simulated via an adjusted Markov chain with the flow *XZ* fixed at the specified age.

The *OE* flow plays a small role in shaping unemployment, but is quite relevant for participation. We can interpret this flow as the job finding probability of workers exerting little effort while searching. These transitions are particularly important for younger and older workers.

5.3. *Controlling for Heterogeneity*

Our results may be affected by compositional changes of the population. In a first attempt to address this potential problem, we control for the presence of cohort, temporal and geographical (state) heterogeneity of worker flows, allowing for interactions between cohort and time. This correction barely affects the magnitude of probability transitions and their relative importance in shaping unemployment and participation over the life cycle. We explain these results in greater detail in the online Appendix, Section E.

5.4. *Time-aggregation Bias*

We also study whether adjusting for time-aggregation bias modifies our results regarding life-cycle decompositions of unemployment and participation rates. Time-aggregation bias refers to the fact that some transitions might not be recorded in the data if the data are collected at fixed intervals of time (every month in the case of the CPS). For example, consider an individual at the beginning of period *t* who is employed, then loses his job and obtains a new one within the same month. At the beginning of period *t* + 1 he appears as employed again, thus we would only record an

EE transition. However, since there were actually two transitions (*EU* and *UE*) during the month, we would be underestimating both *EU* and *UE*. Following Shimer (2012) and Elsby *et al.* (2013), we correct our flows using an eigenvalue-eigenvector decomposition technique (details are in the online Appendix, Section F). While the correction does affect the level of monthly transitions, their shapes and relative importance for determining unemployment and participation profiles over the life cycle remain unaltered.

In addition, we use the time-aggregation correction to address a potential issue with the AB1C method. Because this method is based on modifying a particular transition probability (for instance *EU*), we also need to change the corresponding 'stay' flow (*EE* in our example) to have a well-defined Markov matrix. This procedure affects the persistence of the Markovian process in a potentially relevant way. One may question whether our results are genuinely driven by the change of *EU*, or by the side effect on *EE*. Using time-aggregation correction techniques, we circumvent this problem by constructing transition matrices of very high frequency (hourly) in which the persistence is naturally higher, i.e. the diagonal terms *EE*, *UU* and *OO* are closer to 1. Performing AB1C decompositions under this setting implies a substantially smaller change of off-diagonal flows, and consequently, a much lower proportional effect on the persistence effect on the 'staying' transitions. The results show that the relative importance of flows remains unaltered in this alternative setting. Hence, we conclude that our results are mostly driven by the effect of switching states, rather than the modified persistence of the Markovian process.

5.5. *Misclassification Errors*

Finally, we also study the effect of misclassification errors, since potentially spurious transitions may have a relevant impact on our results. Earlier contributions, i.e. Abowd and Zellner (1985), rely on re-interview data to quantify potential misclassification. Lack of original re-interview data separated by age of the respondent, as well as the lack of updates of these re-interviews make this option infeasible for our purposes.

Here, we use two approaches suggested by the recent literature. First, we apply a technique introduced by Feng and Hu (2013), which relies on observed CPS data and latent variable theory to obtain misclassification probabilities for the different labour market states (*E*, *U*, *O*). The flexibility of this method allows us to correct possible misclassification by age in our sample. We also apply the mechanical correction suggested in Elsby *et al.* (2013), who reclassify one month reversals in unemployment or inactivity. These exercises show that correcting for misclassification generates changes in the levels of the transition probabilities and stocks over the life cycle, but does not alter their overall shapes. More importantly, our conclusions on the relative relevance of flows in the AB1C decomposition are the same. See details in the online Appendix, Section G.

6. Conclusion

In this article, we estimate and report life-cycle transition probabilities across labour market states for male and female workers in the US, using monthly files from the CPS.

We construct measures of worker flows between labour force states by age. This procedure gives us a consistent set of facts from which we can identify age-dependent job finding and separation probabilities, as well as labour force exit/entry probabilities.

Using our estimates, we find that most differences in participation and unemployment rates over the life cycle can be attributed to the probability of leaving employment and the probability of entering unemployment from inactivity. The empirically most relevant flows are the employment exit rates for the young (*EU* and *EO* rates) and the labour force (re)entry flow for older workers, *OU*. These facts hold for males and females. Hence, models trying to explain unemployment and participation over the life cycle should endogenise these transitions. On the other hand, the job finding probability explains little in terms of life-cycle differences.

Nevertheless, we do not identify the fundamental factors causing the high employment exit rates of the young and the low entry rates of the older population. Since our findings hold for diverse groups and are robust to a large variety of measurement problems, we hypothesise that it is possible to provide general mechanisms explaining life-cycle behaviour in the labour market. This is a task future research should focus on.

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Additional Supporting Information may be found in the online version of this article:

Appendix A. Conditional Analysis.
Appendix B. Effects of the Great Recession.
Appendix C. Results for Ages 30–50.
Appendix D. Alternative Decomposition Methods.
Appendix E. Introducing Controls.
Appendix F. Time-Aggregation Results.
Appendix G. Misclassification (MC) Results.
Data S1.

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